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A neural network approach for non-contact defect inspection of flat panel displays

H.A. Abeysundara[a]*, Hiroshi Hamori[a], Takeshi Matsui[b], Masatoshi Sakawa[b]

[a]R&D Division, OHT Inc, 1118-1 Nishichujo, Kannabe-Cho, Fukuyama 720-2123, Japan
[b]*Department of Electrical, Systems and Mathematical Engineering, Faculty of Engineering, Hiroshima University, 1-4-1 Kagamiyama, Higashi Hiroshima 739-8527, Japan*

Abstract

This paper proposes a neural network-based approach for the inspection of electrical defects on thin film transistor lines of flat panel displays. The inspection is performed on digitized waveform data of voltage signals that are captured by a capacitor-based non-contact sensor by scanning over thin film transistor lines on the surface of the mother glass of flat panels. The sudden deep falls (open circuits) or sharp rises (short circuits) on the captured noisy waveform are classified and detected by employing a four-layer feed-forward neural network with two hidden layers. The topology of the network comprises an input layer with two units, two hidden layers with two and three units, and an output layer with one unit; a standard sigmoid function as the activation function for each unit. The network is trained with a fast adaptive back-propagation algorithm to find an optimal set of associated weights of neurons by feeding a known set of input data. The ambiguity of the threshold definition does not arise in this method because it uses only local features of waveform data at and around selected candidate points as inputs to the network, unlike the existing thresholding-based method, which is inherently prone to missed detections and false detections.

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Keywords: Feed-forward neural networks; Error back-propagation; Flat panel display; Open short detection; Non-contact defect inspection

* Corresponding author. Tel.: +081-84-960-2120; fax: +081-84-960-2118.
E-mail address: ha_abey@ohtinc.jp.

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1. Introduction

Amid growing demand for flat panel displays (FPD) in recent years, having a wide range of applications such as televisions, computers, cameras, mobile phones, medical equipments, toys and etc, there is a stiff competition among manufacturers for high throughput product lines and low priced manufacturing. The demand for larger sizes of mother glass (e.g. Generations 10,11,12) as well as the demand for high density thin film transistor (TFT) pitch patterning of FPDs with the emergence of ultra high definition 4K and 8K TVs have also been increasing. However when the pitch pattern density of an FPD is increasing the tendency of defects such as inter layer short circuits between TFT lines is also increasing.

Automatic optical inspection (AOI) methods have been mainly used in the past for defect detection during intermediate processes of fabrication lines of FPDs [1,2]. Though the AOI methods are fast, non-contact and occur no damages to glass substrates, non-electrical defects such as particles on panel surface (micro dusts) and even slight color changes on TFT wirings can also be falsely detected as defects. A major drawback in AOI methods is that it is extremely difficult to discriminate those non-electrical defects from electrical defects (open NG and short NG) that need to be repaired and restored. Furthermore, some common electrical defects, which occur with the increased pitch patterning, such as cracks on wirings and short circuits in between layers under wire crossings cannot be detected properly with AOI methods.

The commonly used pin probed inspection method of which electrode pins make direct contacts on each and every wiring on the panel surface and measure the current flown after applying some voltage. Though this method has the advantage of detecting nothing but electrical defects, it also has disadvantages such as low-speed inspection, poor adjustability of probe fixtures for changes of pitch patterns of TFT lines and the necessity of frequent replacement of pin probe fixtures of inspection machines, which is a costly process.

The non-contact defect inspection method for FPDs proposed by Hamori et al. [3,4,5,6] is the most promising technique so far, utilizing a capacitor-based sensor. The detection of defects in that system becomes detection of sharp rises or deep falls on a waveform of a voltage signal captured by the sensor scanning over TFT lines. The method they are using to detect those defective points on waveforms is a thresholding method after some noise cleaning operations. However determining a proper threshold level to correctly indentify those rises or falls on waveforms is still not easy since such measured voltage signals contain various noises such as random noises, external vibrations and other noises due to environmental effects such as machine temperature.

Therefore, in this paper, we propose an alternative detection method by using an artificial neural network to the above mentioned non-contact inspection method. We employ a 4 layered feed-forward neural network to classify candidate points, which are selected from waveform data and fed to the network, as defective (NG) or non-defective (OK). There is no threshold selection ambiguity involved in this method instead some local and neighborhood characteristics of candidate points are considered as inputs to the network and the network determines if a candidate is defective or not based on prior learning. There are three local features currently used as such inputs, which are Signal to noise ratio (SNR), Residual difference and Change of wave length at a given particular candidate point and its neighborhood. The network is trained using an adaptive error back-propagation algorithm [7] based on gradient descent by feeding a known set of input data comprising every possible pattern of defective and non-defective points on the waveform.

2. Non-contact defect inspection

As illustrated in Fig. 1(a), in the non-contact defects inspection method proposed by Hamori et al., a capacitor-based non-contact sensor utilizes two electrodes, a feeding electrode and a receiving electrode, that scan parallel to each other across TFT lines over the mother glass substrate of FPD panel. During scanning, a small voltage is fed into TFT lines through the feeding electrode and is received through the receiving electrode that captures the voltage signal through an AD converter to the host computer as a digitized waveform.

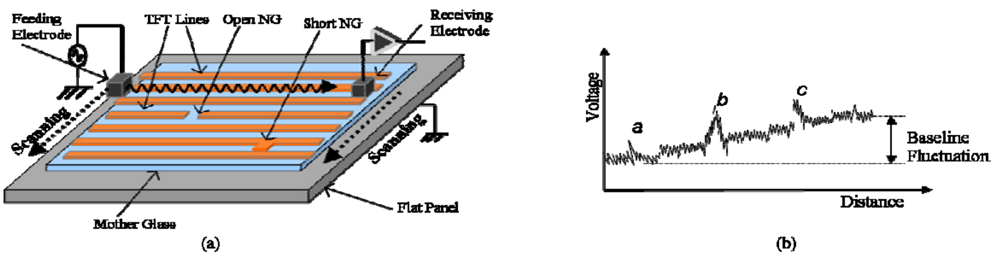

Fig. 1. (a) Non-contact FPD inspection system; (b) Typical pattern of a waveform captured by a non-contact sensor

Fig. 1(b) shows such a typical waveform pattern of a captured voltage waveform through a non-contact sensor. The electrical defects on TFT lines (open NG or short NG) will show sudden sharp rises or deep falls on the waveform and therefore detection of defects would become detecting of those rises and falls on the waveform. Generally such waveforms are mixed with lot of random noises, external vibrations and other artifacts as shown in the figure. The large deviation at point *a* may be a random electrical noise, at point *b* may be a deviation caused due to a real electrical defects and at points *c* may be a vibration caused by an external force. Due to practical reasons in real production environments the gap between the surfaces of the scanning electrodes and the flat panel are not uniformly even. This unevenness causes low frequency swinging or baseline fluctuations on the captured voltage waveform as shown in the figure.

2.1. Defect detection by thresholding

Since the original waveform data captured by a non-contact sensor is noisy, as shown in Fig. 2(a), a moving average filter is applied initially to reduce high frequency random noises (Fig. 2(b)). Then low frequency swinging and baseline fluctuations of the waveform due to the unevenness of the gap between the panel surface and the sensor surface are neutralized by applying a derivative operator with a pre-determined step length (Fig. 2(c)). The resulting waveform is undergone again a moving average operator to remove remaining spike noises. Finally magnitude values of the waveform are compared with a pre-determined threshold value and the points that exceed the threshold level are considered as defect points (Fig. 2c).

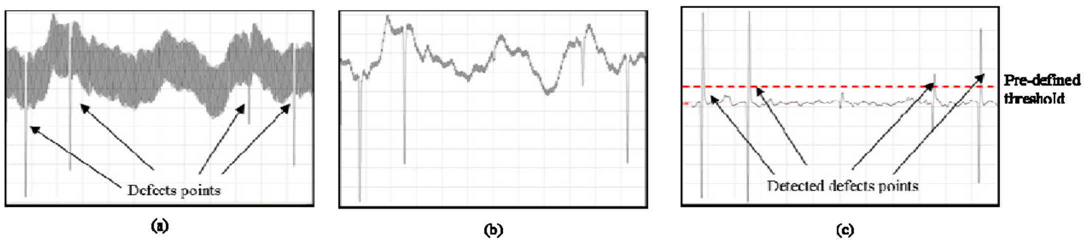

Fig. 2. Defects detection by thresholding method; (a) Original waveform; (b) After noise suppression; (c) Thresholding on differential waveform

2.2. Drawbacks in the thresholding method

The thresholding method described above is quiet appropriate as long as environmental effects such as the machine temperature and factory vibrations and the gap between surfaces of the sensor and the panel remain firmly stationary, which minimizes extra noises and unnecessary deviations on the voltage waveform. However in real production lines the temperature and the external vibrations can vary from time to time and from machine to machine. It can also be varied from location to location of machines even inside the same factory.

Keeping the distance between the sensor and the panel fixed during scanning is also not an easy task, so that the voltage signal shows fluctuations or swinging. All of these factors severely affect the pattern and the noise level of the captured voltage waveform and determining threshold parameters for the software program is a difficult task as shown in Fig. 3. Whenever an inspection machine is changed or its location is changed, operators have to look carefully several waveforms and set threshold parameters manually.

On the other hand, the threshold parameter set by the operator is a global value, which applies to the entire waveform. However most of the above effects to the voltage signal are local effects, in which, taking a global threshold value as the deciding factor in a highly locally dependant feature space is lacking appropriateness.

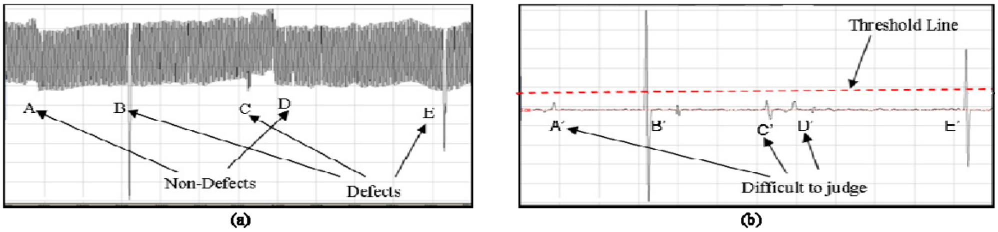

Fig. 3. Difficulty of determining a proper threshold value (a) Original waveform; (b) Differential waveform

As shown in Fig. 3(a), the points *B, C* and *E* are real defect points and points *A* and *D* are not defects but sudden fluctuations due to change of gaps between the sensor and the panel. The corresponding points for real defects on the differentiated waveform (Fig. 3(b)) are *B', C'* and *E'*. Out of these 3 defect points only *B'* and *E'* can be detected using the threshold and point *C'* is difficult to be detected by the threshold although it is actually a defect point. If the threshold level is further lowered the missed detected point *C'* can be detected but in the same time points *A'* and *D'* can also be detected as defects, which will be false detections. In manufacture's standpoint both missed detections and false detections are costly.

This hurdle of determining a proper threshold value is difficult to leap over as long as the threshold value is global and the features around real defect points are local. The lower the threshold value is set the higher the ratio of false detections appear whereas the higher the threshold value is set the higher the ratio of missed detections occur.

3. Proposed method based on a neural network

As described in the section 2.2, in the method proposed by Hamori et al. the criteria of determining a threshold value lacks appropriateness since the feature variations on and around the defect points are largely local features while the threshold is a global value. Hence it requires an adaptive algorithm with a high degree of accuracy and efficiency since the system is largely data driven and the patterns of defect points on waveforms are highly non-linear. The cross correlation method can be used to detect such patterns on waveform data, which is a measure of 'goodness of fit' with a pre-selected pattern. The level of fitness of about 80% or more corresponds to patterns in data that are easily discerned as good matches by the human eye. However having various patterns of waveforms with various patterns of defect points on them it requires to prepare and store hundreds of patterns if not thousands, which would be a huge time consuming exercise. Moreover the features around defect points on waveforms are varied from channel to channel, from location to location and etc. So that a technique such as a neural network that can learn the environmental effects and memorize, must be a much suitable way of addressing the problem. An artificial neural network is an intelligent agent that can handle effectively a large amount of dynamic, non-linear and noisy data [7,8,9]. It also can observe, learn and memorize from the experience before performing a particular task. Therefore the most reliable approach must be such an intelligent approach such as using a neural network since a neural network can be trained by feeding known data before actually put into perform and can keep the adaptability.

3.1. Inputs to the neural network

Since a neural network can be trained by feeding a known set of data, any feature around an input point on the input waveform that can be considered as influential to the output must be considered as an input to the network. By looking at neighborhood characteristics around defective points and non-defective points on waveforms, following three features were identified as inputs to the network (input vector $\underline{\boldsymbol{x}}$), namely Signal to noise ration (SNR), Residual difference, and Change of wave length. All of these input parameters $\underline{\boldsymbol{x}}(x_1,x_2,x_3)$ are picked within a pre-determined length of neighborhoods of possible candidate points on the waveform whereas candidate points are selected by a simple low level threshold such that it may include many false detection but not to miss any of them

3.1.1. SNR

If the characteristics within a neighborhood of a defect point on a waveform are observed (Fig. 4a) it is understood that there is a sharp deviation of magnitude. In other words the level of the signal at a particular point shows a considerable deviation against the level of background noise, which means a change of signal to noise ratio (SNR). Therefore SNR is considered as the first input (x_1) of the input vector $\underline{\boldsymbol{x}}$ and is taken as:

$$x_1 = SNR = \frac{\mu}{\sigma} \tag{1}$$

where μ is the mean value and σ is the standard deviation of the waveform within the selected neighborhood around a candidate point.

3.1.2. Residual Difference

Besides the sharp deviation at the defect point, the neighboring area consisting of a few wave lengths can also be seen deviated towards the same direction as main deviated point (Fig. 4a). This particular feature of the waveform within the neighborhood is measured as the difference of average upper peak level with the regression line (h_1) and the difference of average lower peak level with the regression line (h_2). In other words the residual difference of upper and lower peek levels in the neighborhood is taken as the second input (x_2) of the input vector $\underline{\boldsymbol{x}}$ and is taken as:

$$x_2 = | h_1 - h_2 | \tag{2}$$

3.1.3. Change of wave length

In the original waveform it shows a considerable change of wave length at a defect point (Fig. 4a) and is taken as the next input to the network. Though this wave length change appears in the normal waveform, it is easier to measure on the differentiated waveform as seen in Fig. 4b. So that the rate of change of wave length of a defect point from that of average wave length in the normal area is taken as the third input (x_3) of the input vector $\underline{\boldsymbol{x}}$ and is taken as:

$$x_3 = \frac{|D - d|}{d}, \tag{3}$$

where D is the wave length at the input point and d is the average wave length at neighborhood (Fig. 4b).

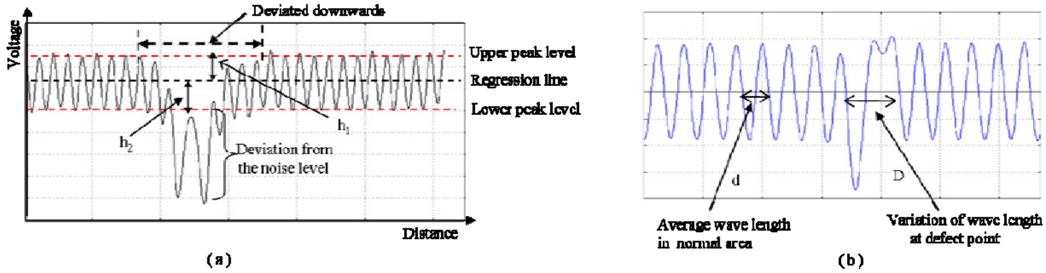

Fig. 4. Picking input data from a neighborhood of a defect point, (a) Measurement of SNR and residual different; (b) Measurement of change of wave length on the differential waveform

3.2. Topology of the network

After testing a numerous topologies of feed-forward neural networks with both single hidden layer and two hidden layers, we have found that the most reliable topology for our problem is a 4-layered feed-forward network such that an input layer with two units, two hidden layers with 2 and 3 units, and an output layer with one unit (Fig. 5). The input feature vector $\underline{x}$ (x_1,x_2,x_3) consists of 3 components , the weight space consists of 27 weights, which is inclusive of weights associated with bias input to each unit, which are not depicted in the figure and the output vector $\underline{y}$ is single component. The total network function *Net* can then be represented as:

$$\underline{y} = Net(\underline{x}) \tag{4}$$

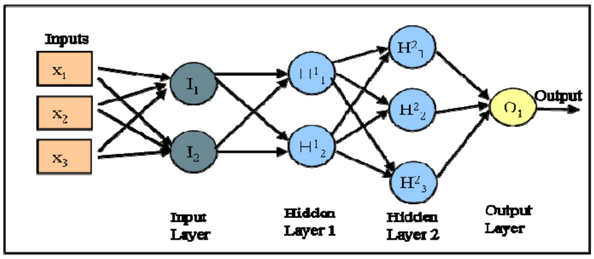

Fig. 5. Topology of the feed-forward neural network

3.3. Activation function

The activation function of each computing unit in the network is in the form of a sigmoid function (logistic function) because training of the network is to be done by error back-propagation algorithm, which requires the activation function to be a continuous function.

Since the back-propagation requires computation of gradients of the error function at each iteration step, the continuity and differentiability of the error function must be guaranteed. Therefore the activation function *f* of each unit in the network is taken as:

$$f(X) = \frac{1}{1+e^{-X}} \quad and \quad X = \sum_{i=1}^{n} w_i x_i \tag{5}$$

where x_i *(i=1,..,n)* are the inputs to the unit (in case of input layer those are the components of the input vector $\underline{\boldsymbol{x}}$, and in case of a hidden or output layer those are outputs from the previous layer) and w_i are the weights associated with each such input.

Then the calculation of an output value *y* from the above network can be explicitly expressed as:

$$y = f(\sum_{l=1}^{3} w_{ol}.(f(\sum_{k=1}^{2} w_{lk}.(f(\sum_{j=1}^{2} w_{kj}.(f(\sum_{i=1}^{3} w_{ji}.x_i + B_j^I)) + B_k^{H1})) + B_l^{H2})) + B^O) \tag{6}$$

where w_{ji} is a weight in input layer connecting i^{th} input and j^{th} neuron, w_{kj} is a weight in hidden layer 1 connecting j^{th} neuron in the input layer and k^{th} neuron in the hidden layer 1, w_{lk} is a weight in hidden layer 2 connecting k^{th} neuron in the hidden layer 1 and l^{th} neuron in the hidden layer 2 and w_{ol} is a weight in the output layer connecting l^{th} neuron in the hidden layer 2 and the output neuron. B_j^I is the bias for the j^{th} neuron in the input layer, B_k^{H1} is the bias for the k^{th} neuron in the hidden layer 1, B_l^{H2} is the bias for the l^{th} neuron in the hidden layer 2 and B^O is the bias for the output neuron. x_i is the i^{th} component of the input vector $\underline{x}$ and f is the common activation function *(5)* of the network.

4. Training the network

A feed-forward neural network is a computational graph whose nodes are computing units and whose directed edges transmit numerical information from node to node. In the network each arrow from left side to right side (Fig. 5) is associated with a synaptic weight and those weight values must be optimized before use in a real situation task. The combination of those weights, which minimizes the error, is said to be the optimal solution to the learning problem. Since there are many weights in the network associating each input in a layer to the each unit in the next layer, we don't know how much each of those weights is to blame for the final error and divvy up the adjustment among these weights proportionately. Therefore this problem can be called a blame assignment problem or a credit assignment problem. The back-propagation solves this problem, as its name depicts it looks for the minimum of the error function in weight space using the method of gradient descent. A set of known inputs comprising both NG points and OK points in all sorts of patterns of input data will be used as the training data set. We also have adopted an adaptation technique [7] in order to accelerate the convergence of the error function. It is an adaptive step algorithm that the step size is increased whenever the algorithm proceeds down the error function over several iterations. When the algorithm moves over a valley of the error function the step size is decreased.

4.1. Training results

Training of the network was carried out with the error back-propagation algorithm by using a set of hand picked data containing 50 defect points (NG) and 50 non-defect points (OK) covering every possible pattern of defect points and non-defect points as shown in Fig. 6. The data were captured by OHT's three different GX-3

High speed LCD/PDP testers in different locations. The 3 input parameters were picked from those selected data points and used as the input data set for offline training of the neural network.

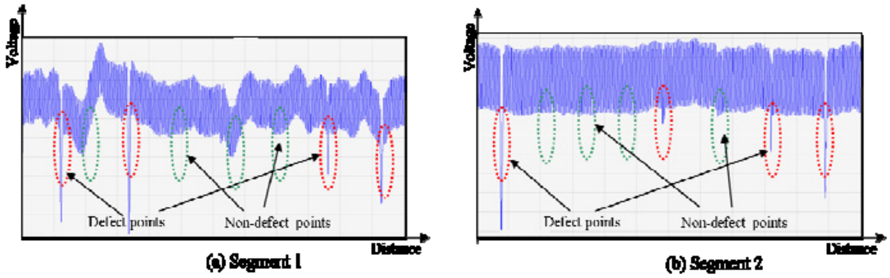

Fig. 6. Two segments of different waveforms used to pick data for network training;

Numerous topologies of feed-forward neural networks with both one hidden layer and two hidden layers were tested to determine the best one for our problem. Error graphs of most of them were either moved a little bit horizontally or fell suddenly and then in both cases converged to a higher level than the excepted level. Fig. 7 shows two of such unacceptable error graphs and a well converged error graph, in which Fig. 7(a) is for a single hidden layer network consisting 3 units, Fig. 7(b) is for a two hidden layer network with 3 and 2 units respectively and Fig. 7(c) for a 2 hidden layer network with 2 and 3 units respectively. As shown, Fig. 7(c) shows the best convergence level, which converges below the set level of 0.01 and therefore it (network of two hidden layers with 2 and 3 units respectively) was selected for our task.

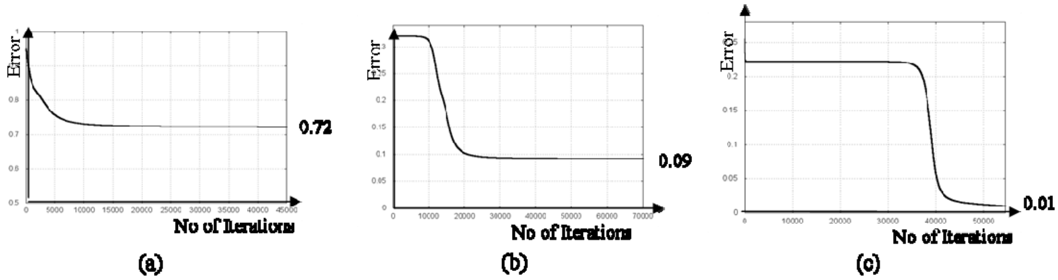

Fig. 7. Error convergence for different network topologies; (a) Single hidden layer with 3 units; (b) 2 hidden layers with 3 and 2 units respectively; (c) 2 hidden layers with 2 and 3 units respectively

Initially all the weight values of the above selected network were randomly set to small values between 0 and 0.1 and the learning constant γ was set to 0.1. The convergence time of the error graph was considerably reduced by using an adaptive technique that adjusts the step length according to flow of the error function.

Table 1. Training parameters

Parameter	Value
No of training data	1
Initial weight values (Random)	0 ～0.1
Initial step size (γ)	0.1
Error convergence limit	0.01
No of iterations	54454

5. Defect detection using the trained neural network

Experiments were carried out to verify performance of our method using 3 types of input data captured from 3 different machines in 3 different factory environments. Candidate points were selected using a lower threshold value than the threshold value used in Hamori et al. method and the three input parameters to the network were picked from those candidate points and entered into the network.

5.1. Detection results

Fig. 8 shows some detection results on 3 different waveform segments and voltage waveforms consisting different levels of random noises, external vibrations and baseline fluctuations on them but were able to detect using our method correctly. The points marked at dashed lines in Fig. 8(a) (both red and blue) are candidates that were selected as inputs to the network, and there were 3 defects (at red dashed lines) detected correctly out of 10 candidates. Similarly, Fig. 8(b) shows 3 defects detected correctly out of 8 candidates and Fig. 8(c) shows 2 defects detected correctly out of 26 candidates.

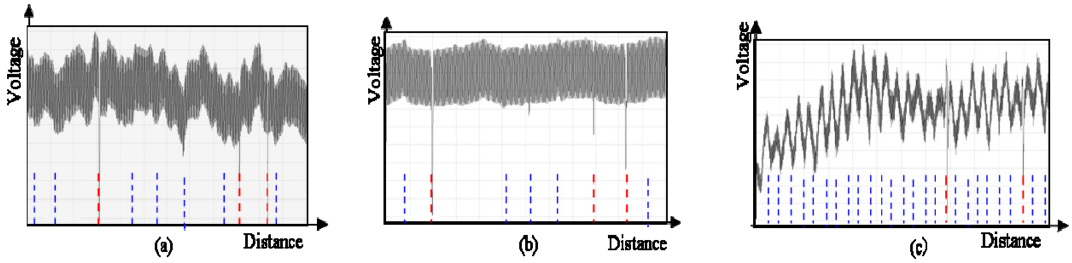

Fig. 8. Detection results on 3 different waveforms captured by 3 different machines in 3 different locations

Table 2 shows a comparison of missed detections and false detections between our method and the old method (existing thresholding method [1,2]) for 3 different data sets. The ratios of missed detections and false detections were able to be reduced considerably. In addition, due to the reduction of ratio of false detections, the number of repairs was able slash drastically and due to the reduction of missed detections, manual check ups were reduced and customer satisfaction was increased. Moreover, manual workload for threshold setting for operators, whenever the machine or the location or the product type to be tested is changed, was also decreased with the use of a trained network. As a result the overall testing time was improved and hence this method can be considered as fast and adaptive.

Table 2. Comparison of missed detections and false detections between old and new methods

	Total defects	Missed detections		False detections	
		Old method	New method	Old method	New method
Data set 1	40	11 (27.5%)	3 (7.5%)	10 (25.0%)	6 (15.0%)
Data set 2	55	13 (23.6%)	3 (5.4%)	16 (29.0%)	7 (12.7%)
Data set 3	36	7 (19.4%)	1 (2.7%)	11 (30.5%)	5 (13.8%)
Total	131	31 (23.6%)	7 (5.3%)	37 (28.2%)	18 (13.7%)

Conclusions

In this paper, we proposed a neural network-based method for non-contact inspection of electrical defects on flat panel displays based on voltage waveform data captured by a capacitor-based non-contact sensor. Our method only uses local features of waveforms within neighborhoods of candidate point as inputs to the network whereas existing method uses a global threshold value, which is prone to more false detections and missed detections. Therefore the threshold selection ambiguity, which is a major drawback in the existing method, does not arise in this method. Following are some achievements that we have confirmed with our experimental results

- Decrease of rate of missed detection to 5% from existing (20%～30%): Missed detection is one of major issues from the manufacture's standpoint as it always affects the quality and the customer satisfaction.
- Decrease of rate of false detections to 15% from existing (20%～30%): The rate of false detections always affect the operators time as it requires manual inspection for final confirmation.
- The manual workload for operators for threshold setting after any change of the machine itself or the environment or the location of the machine were able to slash.

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